In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression,Lasso,Ridge
from sklearn.model_selection import train_test_split as tts
from sklearn.metrics import r2_score as r2, mean_squared_error as mse
from sklearn.preprocessing import StandardScaler
```

In [2]:
```
df= pd.read_csv('Walmart_Store_sales.csv')
df.head()
```

Out[2]:

	Store	Date	Weekly_Sales	Holiday_Flag	Temperature	Fuel_Price	CPI	Unemployment
0	1	05-02-2010	1643690.90	0	42.31	2.572	211.096358	8.106
1	1	12-02-2010	1641957.44	1	38.51	2.548	211.242170	8.106
2	1	19-02-2010	1611968.17	0	39.93	2.514	211.289143	8.106
3	1	26-02-2010	1409727.59	0	46.63	2.561	211.319643	8.106
4	1	05-03-2010	1554806.68	0	46.50	2.625	211.350143	8.106

In [3]:
```
df= df.rename(columns={'Store':'store','Date':'date','Weekly_Sales':'weekly_sales','Hc
                   'Fuel_Price':'fuel_price','CPI':'cpi','Unemployment':'unemployment'
```

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6435 entries, 0 to 6434
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   store         6435 non-null   int64  
 1   date          6435 non-null   object 
 2   weekly_sales  6435 non-null   float64
 3   holiday_flag  6435 non-null   int64  
 4   temp          6435 non-null   float64
 5   fuel_price    6435 non-null   float64
 6   cpi           6435 non-null   float64
 7   unemployment  6435 non-null   float64
dtypes: float64(5), int64(2), object(1)
memory usage: 402.3+ KB
```

1 Basic Statistics Task

1.1 Store with Maximum Sale

In [5]:
```
print('Store with Highest Sale')
print((df.groupby('store').sum('weekly_sales').sort_values('weekly_sales',ascending=Fa
```

```
Store with Highest Sale
store
20    3.013978e+08
4     2.995440e+08
14    2.889999e+08
Name: weekly_sales, dtype: float64
```

1.2 Highest Standard Deviation in weekly_sales for top 3 Stores

In [6]:
```
std_df= df.groupby('store').agg({'weekly_sales':['std','mean']}).sort_values(('weekly_
std_df['coefficient_Of_variance']= std_df[('weekly_sales','std')]/std_df[('weekly_sale
print('\nStore with Highest Standard Deviation in Sales')
print(std_df.iloc[:3])
```

```
Store with Highest Standard Deviation in Sales
        weekly_sales               coefficient_Of_variance
                 std          mean
store
14     317569.949476  2.020978e+06               15.713674
10     302262.062504  1.899425e+06               15.913349
20     275900.562742  2.107677e+06               13.090269
```

1.3 Highest Growth rate for top 3 Stores in Q3 2012

In [7]:
```
df['date']= pd.to_datetime(df['date'],format='%d-%m-%Y')
```

In [8]:
```
from datetime import datetime as dt
q2_start= dt(2012,4,1)
q2_end= dt(2012,6,30)
q3_start= dt(2012,7,1)
q3_end= dt(2012,9,30)
```

In [9]:
```
q2_df= df[df['date'].between(q2_start,q2_end)][['store','weekly_sales']]
q3_df= df[df['date'].between(q3_start,q3_end)][['store','weekly_sales']]
```

In [10]:
```
quarters_df= q3_df.groupby('store').sum('weekly_sales').sort_index()
quarters_df= quarters_df.rename(columns={'weekly_sales':'q3_sales'})
quarters_df['q2_sales']= q2_df.groupby('store').sum('weekly_sales')['weekly_sales'].sc
quarters_df['growth_rate']= (quarters_df.q3_sales-quarters_df.q2_sales)/quarters_df.q2
quarters_df.sort_values('growth_rate',ascending=False).iloc[:3]
```

Out[10]:

store	q3_sales	q2_sales	growth_rate
7	8262787.39	7290859.27	0.133308
16	7121541.64	6564335.98	0.084884
35	11322421.12	10838313.00	0.044666

1.4 Holiday and Non-Holidays AVG Sales comparision

In [11]:

```
df.groupby('holiday_flag')['weekly_sales'].mean()
```

Out[11]:

```
holiday_flag
0    1.041256e+06
1    1.122888e+06
Name: weekly_sales, dtype: float64
```

In [12]:

```
ch1 = dt(2010,12,31)
ch2 = dt(2011,12,30)
ch3 = dt(2012,12,28)
ch4 = dt(2013,12,27)

th1= dt(2010,11,26)
th2= dt(2011,11,25)
th3= dt(2012,11,23)
th4= dt(2013,11,29)

la1= dt(2010,9,10)
la2= dt(2011,9,9)
la3= dt(2012,9,7)
la4= dt(2013,9,6)

su1= dt(2010,2,12)
su2= dt(2011,2,11)
su3= dt(2012,2,10)
su4= dt(2013,2,8)
```

In [13]:

```
christmas_mean_df= df[(df['date']== ch1) | (df['date']== ch2) | (df['date']== ch3) | (
thanksgiving_mean_df= df[(df['date']== th1) | (df['date']== th2) | (df['date']== th3)
labourday_mean_df= df[(df['date']== la1) | (df['date']== la2) | (df['date']== la3) | (
superbowl_mean_df= df[(df['date']== su1) | (df['date']== su2) | (df['date']== su3) | (
```

In [14]:

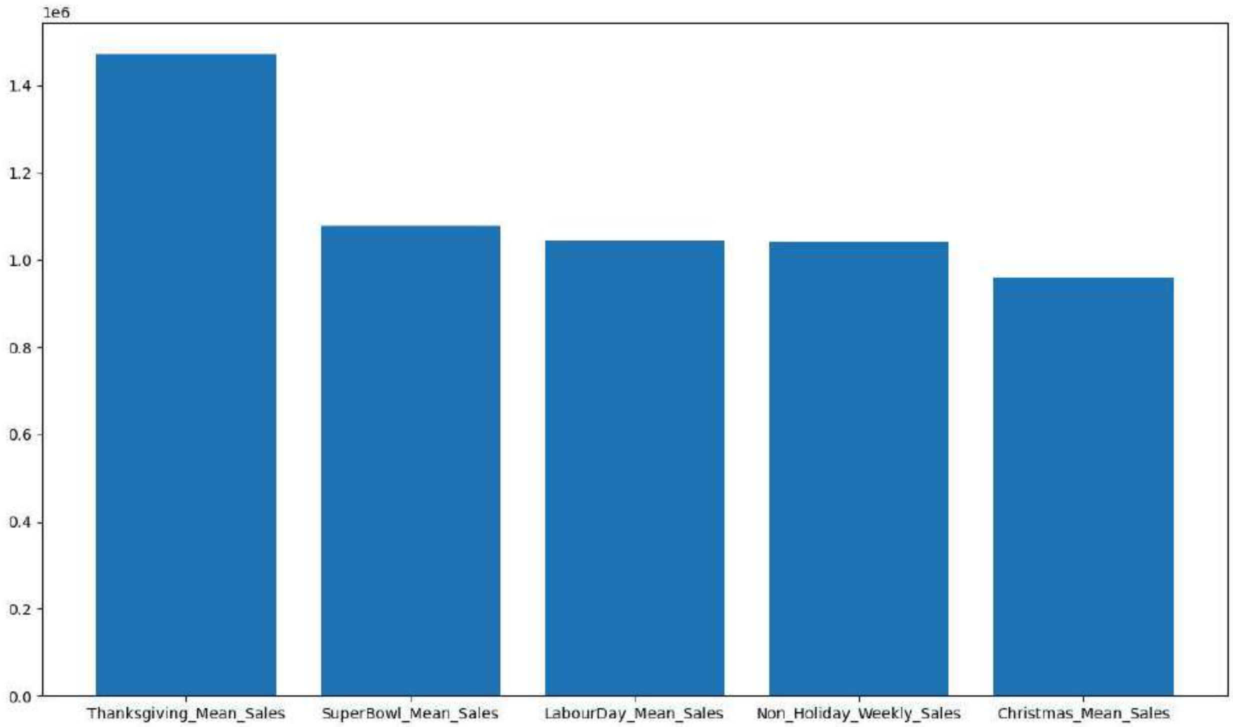
```
dict_mean_sales = {'Thanksgiving_Mean_Sales': thanksgiving_mean_df['weekly_sales'].mea
                   'SuperBowl_Mean_Sales': superbowl_mean_df['weekly_sales'].mean(),
                   'LabourDay_Mean_Sales' : labourday_mean_df['weekly_sales'].mean(),
                   'Non_Holiday_Weekly_Sales' : df[df['holiday_flag'] == 0 ]['weekly_s
                   'Christmas_Mean_Sales' : christmas_mean_df['weekly_sales'].mean()}
```

Only Christmas in Holidays has bad AVG sales than Non-Holiday days

In [15]:

```
plt.figure(figsize=(14,8),dpi=100)
plt.bar(x=dict_mean_sales.keys(), height=dict_mean_sales.values())
```

Out[15]: <BarContainer object of 5 artists>

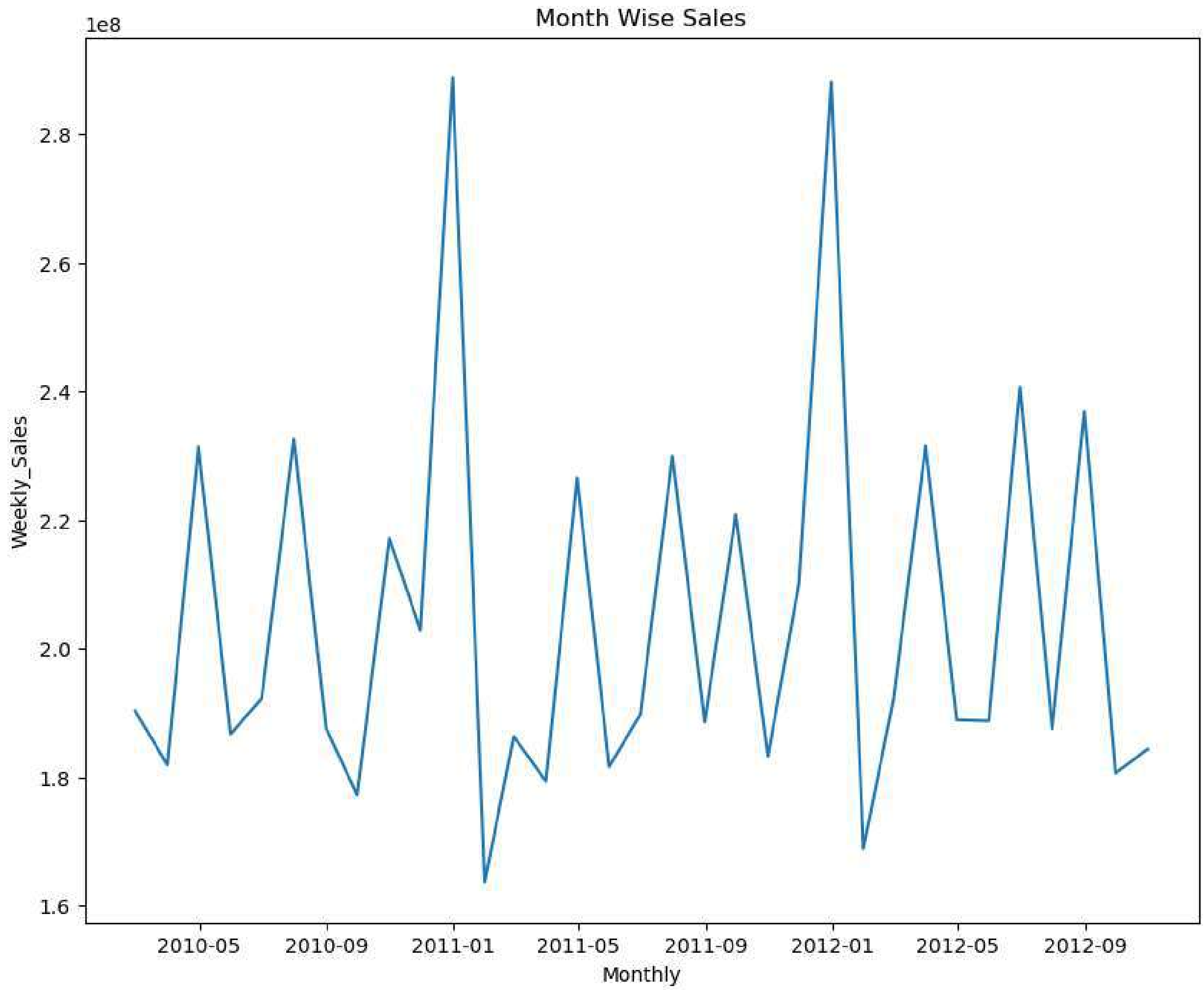


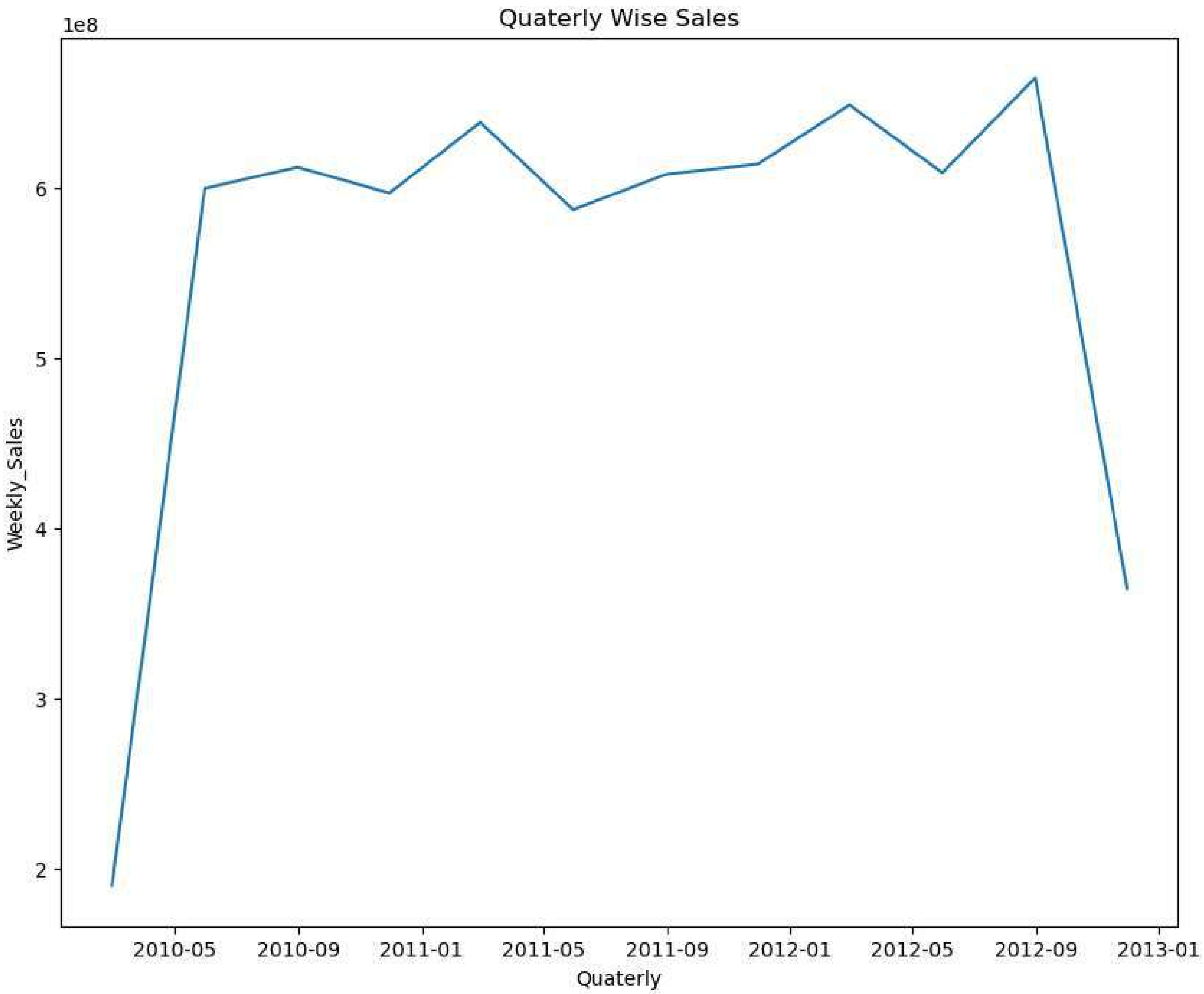
1.5 Monthly, Quarterly, Semester-wise Sale Analysis

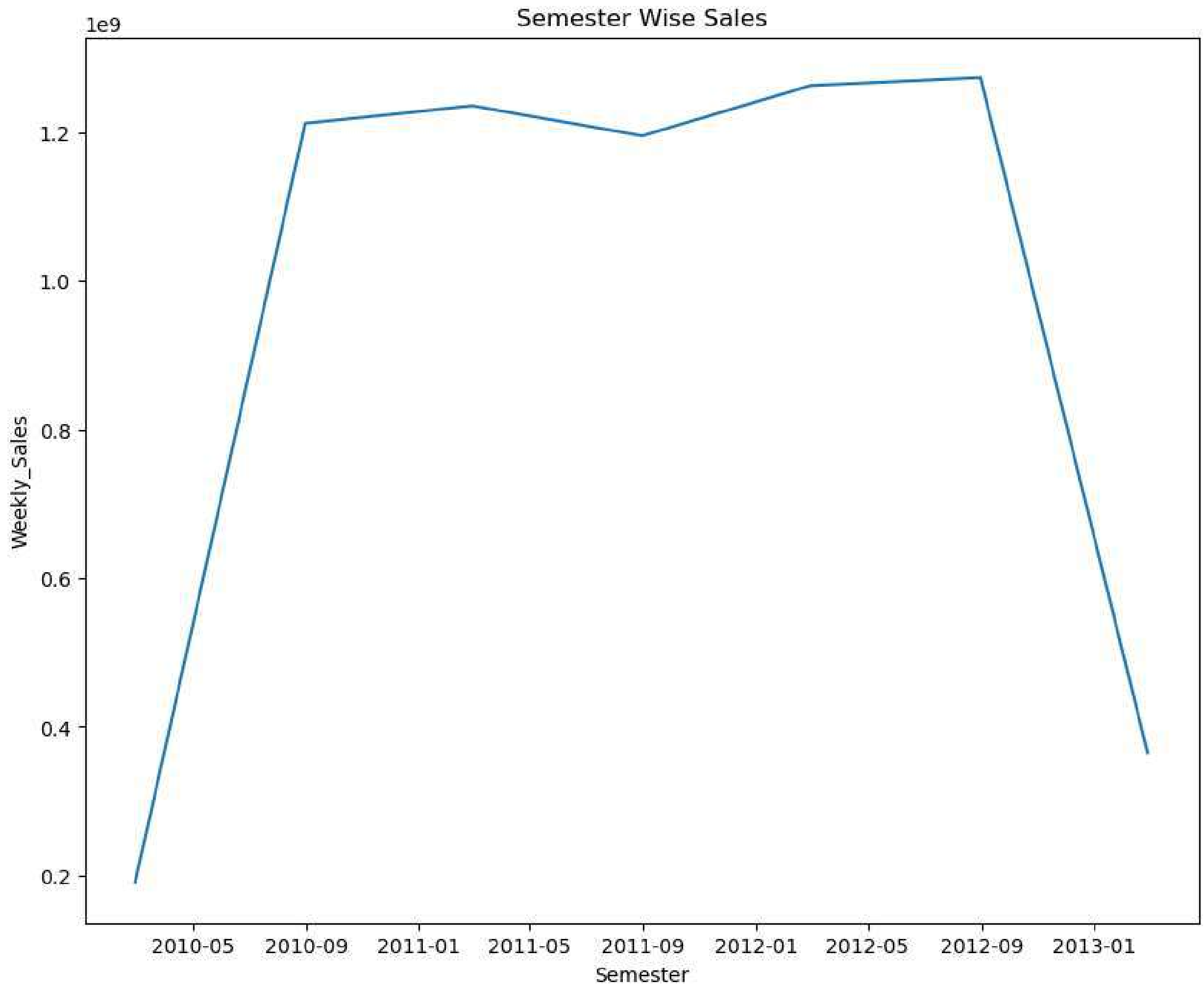
In [16]:

```
monthly= df.groupby(pd.Grouper(key='date', freq='1M')).sum()
monthly= monthly.reset_index()
fig,ax= plt.subplots(figsize=(10,8))
plt.plot(monthly['date'],monthly['weekly_sales'])
plt.title('Month Wise Sales')
plt.xlabel('Monthly')
plt.ylabel('Weekly_Sales')

quaterly= df.groupby(pd.Grouper(key='date', freq='3M')).sum()
quaterly= quaterly.reset_index()
fig,ax= plt.subplots(figsize=(10,8))
plt.plot(quaterly['date'],quaterly['weekly_sales'])
plt.title('Quaterly Wise Sales')
plt.xlabel('Quaterly')
plt.ylabel('Weekly_Sales')

semester= df.groupby(pd.Grouper(key='date', freq='6M')).sum()
semester= semester.reset_index()
fig,ax= plt.subplots(figsize=(10,8))
plt.plot(semester['date'],semester['weekly_sales'])
plt.title('Semester Wise Sales')
plt.xlabel('Semester')
plt.ylabel('Weekly_Sales')
```

Out[16]: Text(0, 0.5, 'Weekly_Sales')


Month Wise Sales
1e8
2.8
2.6
2.4
2.2
2.0
1.8
1.6
Weekly_Sales
2010-05
2010-09
2011-01
2011-05
2011-09
2012-01
2012-05
2012-09
Monthly


Quaterly Wise Sales
1e8
6
5
4
3
2
Weekly_Sales
2010-05
2010-09
2011-01
2011-05
2011-09
2012-01
2012-05
2012-09
2013-01
Quaterly



2 Statistical Models

2.1 Linear Regression Models

In [17]:
```
data= df[df.store==1]
data['date']= np.arange(1,144)
scaler= StandardScaler()
scaler.fit(data)
data.head()
```

```
C:\Users\admin\AppData\Local\Temp\ipykernel_10744\2008928399.py:2: SettingWithCopyWar
ning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/us
er_guide/indexing.html#returning-a-view-versus-a-copy
  data['date']= np.arange(1,144)
```

Out[17]:

	store	date	weekly_sales	holiday_flag	temp	fuel_price	cpi	unemployment
0	1	1	1643690.90	0	42.31	2.572	211.096358	8.106
1	1	2	1641957.44	1	38.51	2.548	211.242170	8.106
2	1	3	1611968.17	0	39.93	2.514	211.289143	8.106
3	1	4	1409727.59	0	46.63	2.561	211.319643	8.106
4	1	5	1554806.68	0	46.50	2.625	211.350143	8.106

In [18]:

```
y= data.weekly_sales
X= data.drop(columns=['weekly_sales','store','date'])
X_train,X_test,y_train,y_test= tts(X,y,test_size=0.2,random_state=42)
```

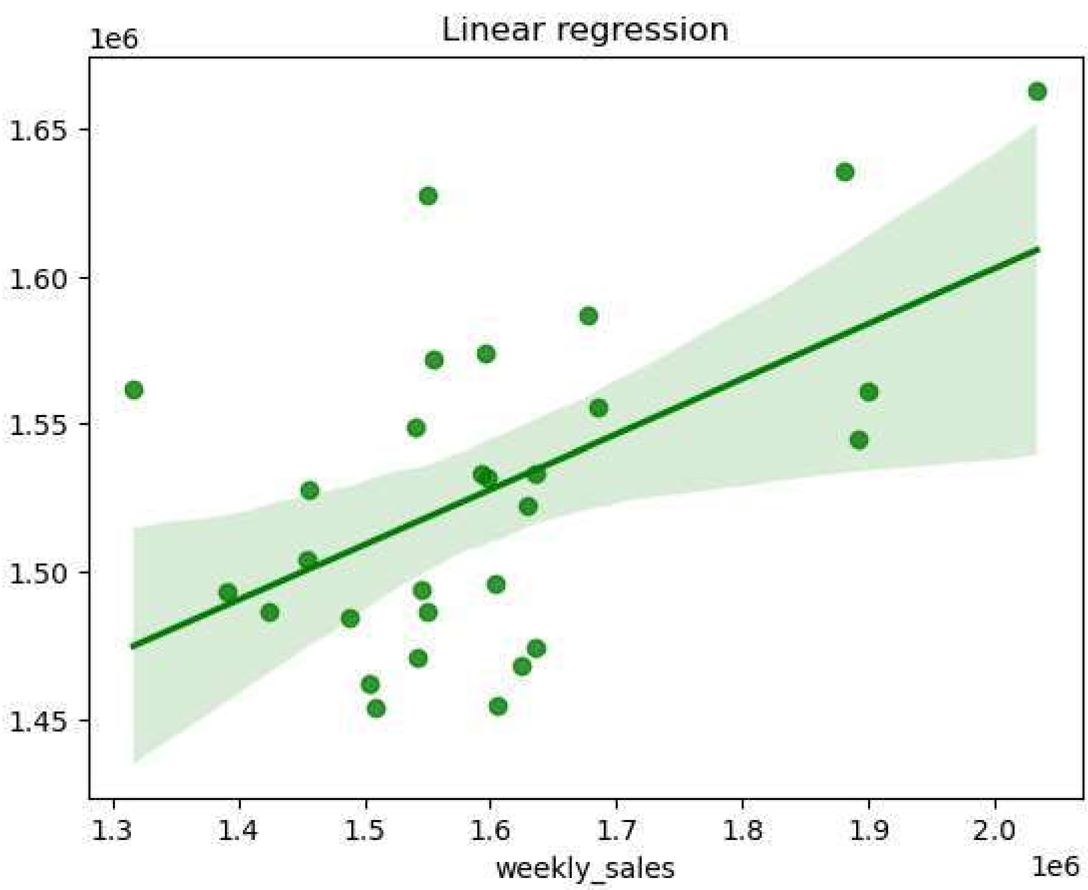
In [19]:

```
model= LinearRegression()
model.fit(X_train,y_train)
y_test_pred= model.predict(X_test)
print('Root Mean Squared Error(RMSE):\n', np.sqrt(mse(y_test, y_test_pred)))
print('R-Squared:\n',r2(y_test,y_test_pred))
plt.title('Linear regression')
sns.regplot(x=y_test,y=y_test_pred,color='green')
```

```
Root Mean Squared Error(RMSE):
 152799.6222036366
R-Squared:
 0.034707216167411015
```

Out[19]:

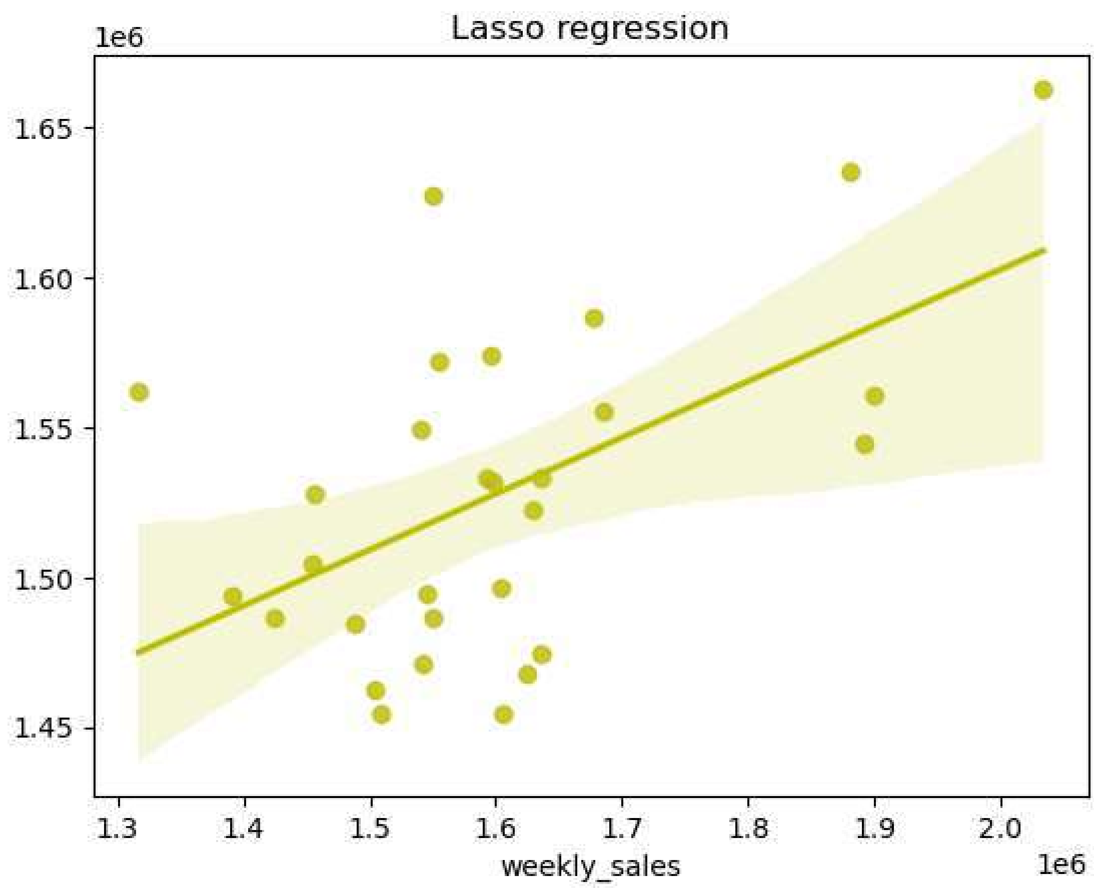
```
<Axes: title={'center': 'Linear regression'}, xlabel='weekly_sales'>
```



In [20]:
```
lasso_reg=Lasso(alpha=1)
lasso_reg.fit(X_train,y_train)
lasso_y_pred=lasso_reg.predict(X_test)
print('Root Mean Squared Error(RMSE):\n', np.sqrt(mse(y_test, lasso_y_pred)))
print('R-Squared:\n',r2(y_test,lasso_y_pred))
plt.title('Lasso regression')
sns.regplot(x=y_test,y=lasso_y_pred,color='y')
```

```
Root Mean Squared Error(RMSE):
 152801.3455588893
R-Squared:
 0.03468544187573952
```

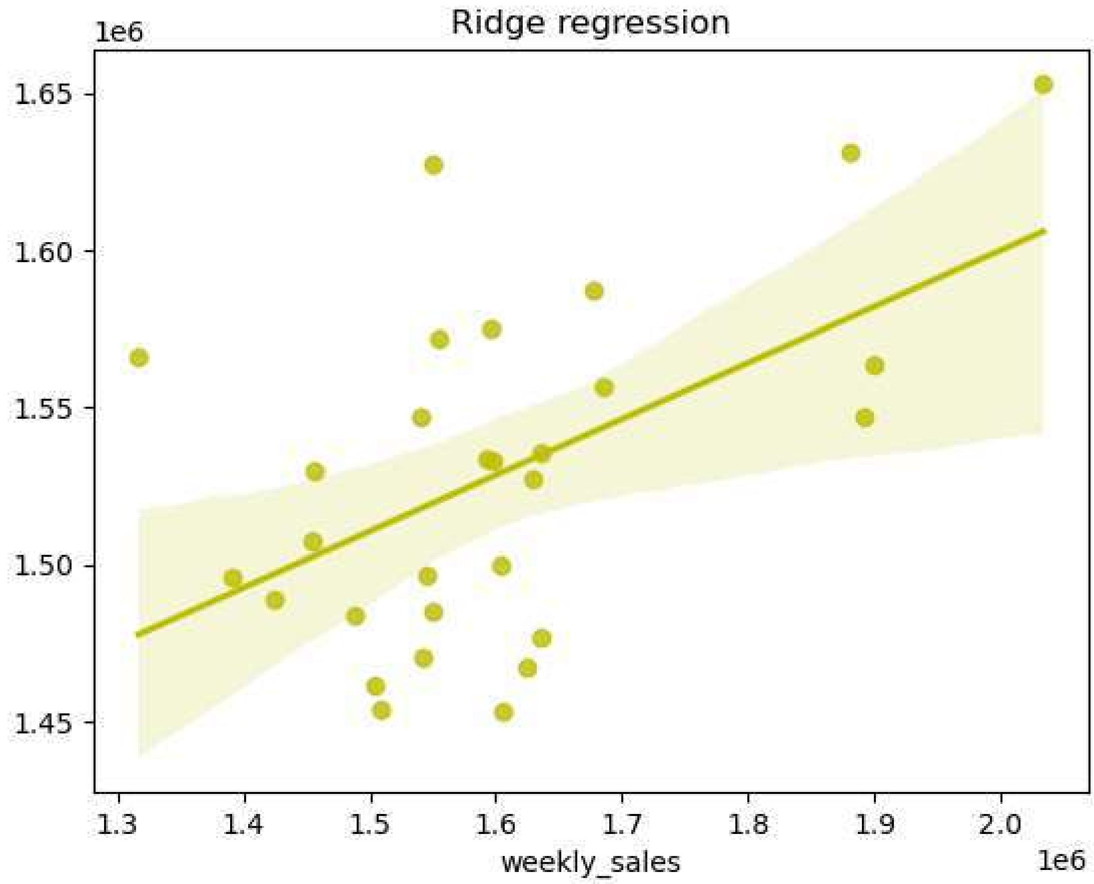
Out[20]:
```
<Axes: title={'center': 'Lasso regression'}, xlabel='weekly_sales'>
```



In [21]:
```
ridge_reg= Ridge(alpha=1)
ridge_reg.fit(X_train,y_train)
ridge_y_pred= ridge_reg.predict(X_test)
print('Root Mean Squared Error(RMSE):\n', np.sqrt(mse(y_test, ridge_y_pred)))
print('R-Squared:\n',r2(y_test,ridge_y_pred))
plt.title('Ridge regression')
sns.regplot(x=y_test,y=ridge_y_pred,color='y')
```

```
Root Mean Squared Error(RMSE):
 153500.45817498674
R-Squared:
 0.025832019326815225
```

Out[21]:
```
<Axes: title={'center': 'Ridge regression'}, xlabel='weekly_sales'>
```



Comparing Coefficient of Regression

In [22]:
```
model.coef_
```

Out[22]:
```
array([ 61993.93468347,  -2617.60358042, -34338.15293787,  13422.2576375 ,
        42279.48782025])
```

In [23]:
```
lasso_reg.coef_
```

Out[23]:
```
array([ 61981.19739554,  -2617.81139176, -34315.03465077,  13418.36841804,
        42250.22731354])
```

In [24]:
```
ridge_reg.coef_
```

Out[24]:
```
array([ 55418.46643272,  -2685.2272262 , -28648.03740797,  12409.08802479,
        34293.58901002])
```

Regression Coefficient for Fuel_Price is reducing accuracy of model in comparision with CPI and Unemployment so we drop it

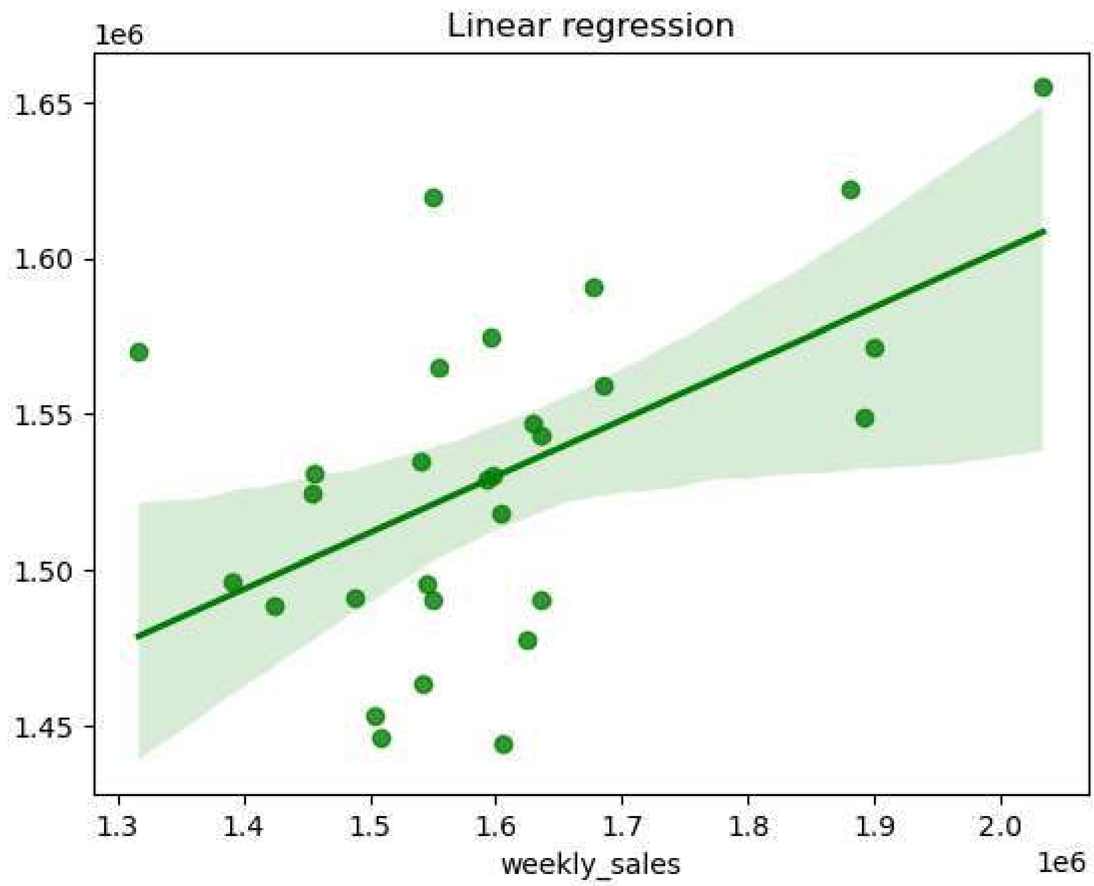
In [25]:
```
y= data.weekly_sales
X= data.drop(columns=['weekly_sales','store','date','fuel_price'])
X_train,X_test,y_train,y_test= tts(X,y,test_size=0.2,random_state=42)
```

In [26]:
```
model= LinearRegression()
model.fit(X_train,y_train)
y_test_pred= model.predict(X_test)
print('Root Mean Squared Error(RMSE):\n', np.sqrt(mse(y_test, y_test_pred)))
print('R-Squared:\n',r2(y_test,y_test_pred))
```

```
plt.title('Linear regression')
sns.regplot(x=y_test,y=y_test_pred,color='green')
```

```
Root Mean Squared Error(RMSE):
 152260.04079652095
R-Squared:
 0.041512656979042495
```

Out[26]: `<Axes: title={'center': 'Linear regression'}, xlabel='weekly_sales'>`

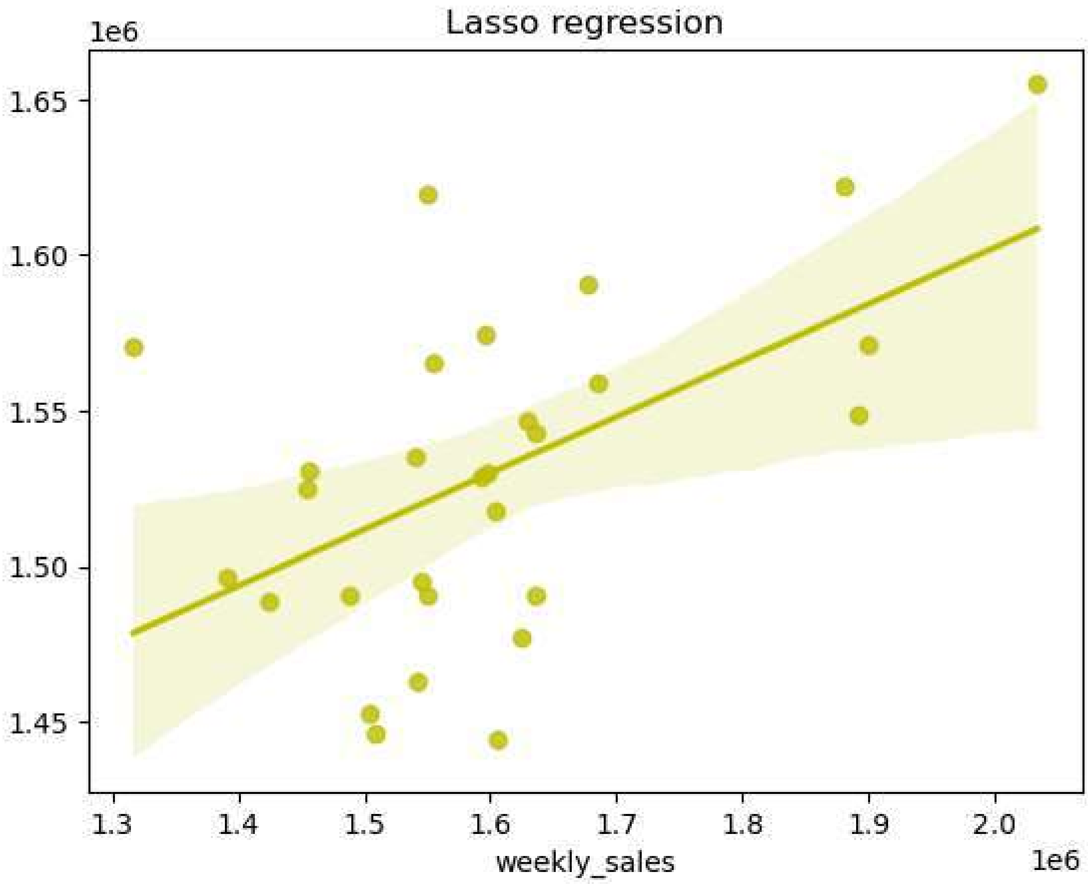


In [27]:

```
lasso_reg=Lasso(alpha=1)
lasso_reg.fit(X_train,y_train)
lasso_y_pred=lasso_reg.predict(X_test)
print('Root Mean Squared Error(RMSE):\n', np.sqrt(mse(y_test, lasso_y_pred)))
print('R-Squared:\n',r2(y_test,lasso_y_pred))
plt.title('Lasso regression')
sns.regplot(x=y_test,y=lasso_y_pred,color='y')
```

```
Root Mean Squared Error(RMSE):
 152262.39307026667
R-Squared:
 0.04148304130290403
```

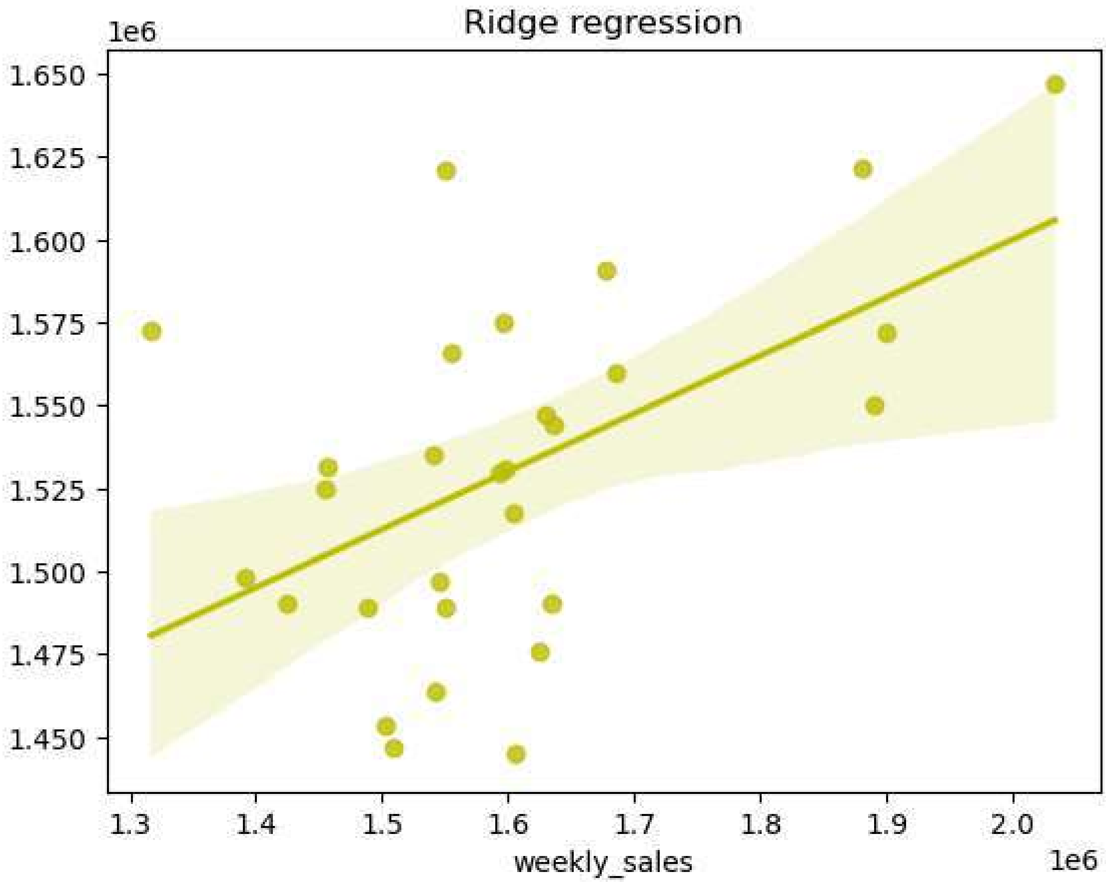
Out[27]: `<Axes: title={'center': 'Lasso regression'}, xlabel='weekly_sales'>`



In [28]:
```
ridge_reg= Ridge(alpha=1)
ridge_reg.fit(X_train,y_train)
ridge_y_pred= ridge_reg.predict(X_test)
print('Root Mean Squared Error(RMSE):\n', np.sqrt(mse(y_test, ridge_y_pred)))
print('R-Squared:\n',r2(y_test,ridge_y_pred))
plt.title('Ridge regression')
sns.regplot(x=y_test,y=ridge_y_pred,color='y')
```

```
Root Mean Squared Error(RMSE):
 153007.1958681327
R-Squared:
 0.032082792684975825
```

Out[28]:
```
<Axes: title={'center': 'Ridge regression'}, xlabel='weekly_sales'>
```



Linear Regression Model give the best performance on test case

2.2 Creating Day column from Date in the Dataframe

We cannot utilize DAY column in ML models as there is only 1 unique value in the whole column

In [29]:
```
df['days']= df.date.dt.dayofweek
df.days= df.days.map({0:'Monday',
             1:'Tuesday',
             2:'Wednesday',
             3:'Thursday',
             4:'Friday',
             5:'Saturday',
             6:'Friday',})
```

In [30]:
```
df.head()
```

Out[30]:

	store	date	weekly_sales	holiday_flag	temp	fuel_price	cpi	unemployment	days
0	1	2010-02-05	1643690.90	0	42.31	2.572	211.096358	8.106	Friday
1	1	2010-02-12	1641957.44	1	38.51	2.548	211.242170	8.106	Friday
2	1	2010-02-19	1611968.17	0	39.93	2.514	211.289143	8.106	Friday
3	1	2010-02-26	1409727.59	0	46.63	2.561	211.319643	8.106	Friday
4	1	2010-03-05	1554806.68	0	46.50	2.625	211.350143	8.106	Friday

In [ ]: